Uncertainties in LCA (Subject Editor: Andreas Ciroth)

Uncertainty in Impact and Externality Assessments

Implications for Decision-Making

Manfred Lenzen

ISA, School of Physics, A28, The University of Sydney NSW 2006, Australia

Corresponding address (m.lenzen@physics.usyd.edu.au)

DOI: http://dx.doi.org/10.1065/lca2005.04.201

Abstract

Goal, Scope and Background. Many disciplines, amongst them LCIA, environmental impact and external cost assessments, are often faced with evaluating trade-offs between two or more alternative options in terms of a range of incommensurable indicators. Using process modeling and valuation, these indicators are quantified at mid- or endpoint levels. Recent discussion amongst LCA experts showed that because of the mutually exclusive aspects of uncertainty and relevance, the midpoint/endpoint debate is controversial and difficult to reconcile. This article is aimed at a more quantitative analysis of mid- and endpoint impacts, and the implications of uncertainty for decision-making.

Methods. The consequences for decision-making of uncertainties of endpoints are analysed quantitatively for the example of ExternE results, by employing statistical hypothesis testing. The Analytic Hierarchy Process (AHP) is then used to demonstrate the use of multi-criteria techniques at midpoint levels.

Results and Discussion. Statistical hypothesis testing at the endpoint level shows that for the ExternE example, probabilities of mistakenly favouring one alternative over another when they are in reality indistinguishable can be as high as 80%. Therefore, the best estimate of external cost is inadequate for most policy making purposes. Indicators at midpoint levels are more certain, but since they are only 'proxy attributes', they carry a hidden uncertainty in their relevance.

Conclusion. If endpoint information is too uncertain to allow a decision to be made with reasonable confidence, then the assessment can be carried out in midpoint terms. However, midpoint indicators are generally further removed from people's experience, and less relevant to the question that people actually want to solve. Nevertheless, if this ultimate question is unanswerable (within the certainty required by the decision-maker), a decision can be made on the basis of stakeholders' subjective judgments about the more certain midpoint levels. The crucial point is that these judgments are able to intuitively incorporate many aspects that impact modeling and valuation has trouble quantifying, such as perceived risk, distribution of burdens and benefits, equity, ethical, moral, religious and political beliefs and principles, immediacy and reversibility of potential impacts, voluntariness, controllability and familiarity of exposure, or perceived incompleteness of human knowledge.

Keywords: Endpoint; externality assessment; midpoint; multi-criteria decision-making; uncertainty; valuation

Introduction

There is an abundance of situations, where a comparative assessment of two or more alternative options (products, companies, projects, industry sectors), in terms of a range of social, economic and environmental indicators has to be carried out. Examples are external cost assessment, industry benchmarking, environmental impact assessment, or life-cycle assessment (LCA).

Indicators featuring in these assessments are often not readily quantifiable, such as biodiversity or community participation. Even if they are quantifiable, many indicators such as noise and emissions are incommensurable, that is they possess different units that cannot be added together. For example, a life-cycle impact assessment can conclude with several numbers pertaining to different impact categories.

In a comparative assessment based on more than one category, one alternative will generally not score better than another in all categories, but instead there are likely trade-offs between the alternatives, so that a clear preference cannot readily be identified. While according to ISO 14042 the aggregation of different impacts into a single number is only optional, a single, aggregate measure of impact or performance, which is easy to interpret and communicate to stakeholders and the general public, is often desired by decision-makers. As a result, a number of concepts have been devised that yield such measures, for example the sustainable process index [1], the ecological footprint [2], or the eco-indicator [3].[1] Approaches taken in some of these concepts are often roughly classified into two categories: process modeling and valuation.

Process modeling is guided by a systemic-holistic view: an empirical causal description of the interactions of all relevant observable natural and socio-economic processes is attempted. In LCA for example (see Fig. 4 in [9]), 'interventions' (such as CO_2 and other emissions, land, energy and resource use etc) are defined, and followed through complex 'impact pathways' using fate modeling, via 'midpoints' (sea level rise, ecotoxicology, eutrophication etc) to 'end-

[1] Such indicators have especially been discussed within LCA. For a summary see [4], for a comparative assessment [5–7], for a critique [8].

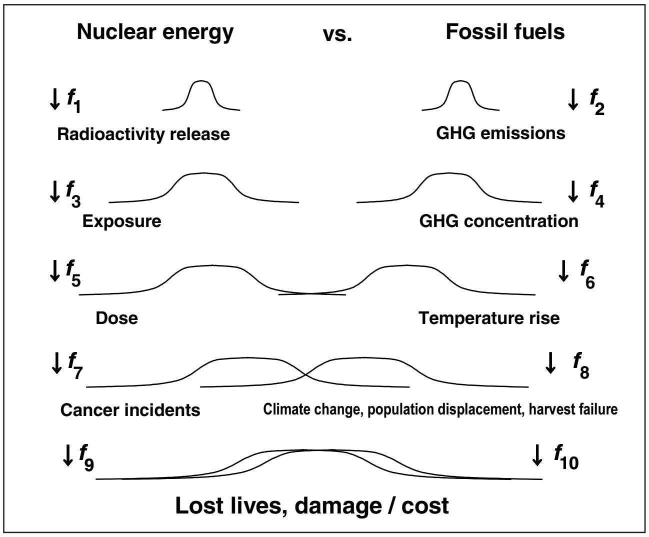

Fig. 1: Example for two mutually exclusive impact pathways ending in a common endpoint measure. Conversions between outputs (energy) and impact measures (emissions, radioactivity etc) are represented by characterisation factors f_i. The uncertainty of these factors causes the uncertainty of subsequent impact measures to increase. Eventually, the high degree of overlap of the bell-shaped value distributions precludes decision-making

points'[2] (damage and loss of human and non-human life, loss of resources etc) relating to certain safeguard objects (human health, ecosystem health, resource base).[3] Impacts can be determined as ex-post average values, or as ex-ante, marginal effects of changes in underlying parameters.

An impact pathway of a nuclear power plant could for example start at the release of radioactivity during normal operation and as a consequence of accidents, via exposure to human and non-human life, leading to doses in tissue, causing incidents of cancer or other radiation-related diseases, resulting in lost or injured lives (**Fig. 1**). A similar pathway could be set up for a fossil-fuelled power plant, with radioactivity stemming from the fly ash. A completely separate, or mutually exclusive impact pathway for the fossil-fuelled plant could start at the emission of greenhouse gases, raising concentrations and radiative forcing in the atmosphere, leading to global warming, climate change, vegetation zone shifts, and sea level rise, causing population displacement, harvest failures, and water quality and availability deterioration, resulting in lost or injured lives. Once again, a similar pathway could be set up for the nuclear plant, with greenhouse gases embodied in the plant's components, or emitted during the plant's operation. While the radioactivity impacts represent the dominant pathway for the nuclear plant, greenhouse gas impacts constitute the priority pathway for the fossil plant.

The term 'valuation' as used in this work shall refer to normative techniques attempting to elicit human preferences, judgment and values, in relation to commodities or (dis)-amenities not traded in a market. The perspective taken in valuation methods is essentially human-centric, and thus deals with revealed preferences (hedonic price, travel or averting cost methods) or stated preferences (contingent valuation or conjoint analysis). A typical valuation exercise could aim at establishing either a relative ranking of attributes and alternatives that is consistent with stakeholders' behaviour, utility, or preferences, or it could attempt monetisation by determining for example willingness to pay, willingness to accept (compensation)[4], shadow prices, or net present value in absolute (monetary) terms.

A mixture of process modeling and valuation is often applied, with the latter techniques usually being applied to aggregate endpoint levels [3,13,14]. An example for such an approach is the well-known ExternE project of the European Commission and the US Department of Energy [15,16], which seeks to develop an impact path methodology for the estimation and comparison of the environmental externality cost of various fuel cycles for electricity generation. While impact pathways are followed through to lost and injured lives, the conversion into associated external cost (the endpoint) is based on valuation. Hertwich [17] notes that values are in principle present even in parts of process modeling, an example being Global Warming Potentials, which are based on a chosen time horizon.

This article is aimed at analysing the implications for decision-making of uncertainty at mid- and endpoint stages in impact or externality assessments. The following Section sets the scene by describing the causes of such uncertainties. The consequences for decision-making of uncertainties at endpoints are then quantified for the example of ExternE results, by employing statistical hypothesis testing. The Analytic Hierarchy Process (AHP) is then used to demonstrate the use of multi-criteria techniques at midpoint levels. Thereafter, advantages and disadvantages of endpoints and midpoints are discussed as certainty/relevance trade-offs, recommendations are made, and the article is concluded. A general aim of the article is to be a source of links to the literature, through frequent references for further reading on the numerous aspects of the topic.

1 Uncertainty in Impact and Externality Assessments

Determining impacts, externalities or damage cost using process modeling and valuation is associated with considerable uncertainties,[5] arising from a range of (overlapping)

[2] In this work, the term 'endpoint' is applied to aggregate measures at the end of one, or several converging impact pathways. This usage may be different from other usages of this term, for example in Environmental Risk Assessment. It also differs from one reviewer's view that endpoints are characterised by the fact that they must be perceivable for decision-makers. This reviewer also remarked that the ecoindicator [3] and the ExternE study [15,16] do not necessarily fulfil this condition. The question asked in this work is whether prohibitive uncertainty precludes moving further along the impact pathways, no matter whether endpoints are perceivable or not.

[3] An alternative terminology could be 'stresses' affecting 'environmental quality' leading to 'receptor effects' that can be converted in to monetary damages [10].

[4] Willingness to pay and willingness to accept can differ due to income and substitution effects [11], and due to loss aversion and status quo bias [12].

[5] Similar qualifications are also applicable to attempts to valuate biodiversity, natural capital, or ecosystem services [18,19].

Table 1: Causes and examples of uncertainty within process modeling and valuation. Acronyms in brackets denote the type of uncertainty [20,21]: C – choice/subjectivity, E – epistemological/unknown facts, M – methodological/model, P – technical/parameter

Cause of uncertainty – Examples
PROCESS MODELING
Complexity of nature, lack of knowledge, and inadequacy of models [93]
Linearisation of non-linear relationships between processes [9] and complicated temporal effects [94], such as
– the global carbon cycle and atmospheric dynamics [24], especially for chemically active gas species [36,41] (M)
– disturbance of ecosystems and resilience [95] (M)
– extrapolation of dose-response relationships towards low doses, especially integration of stochastic effects of low-level radiological doses [96] (M)
Omission of interactions between impact compartments when using partial models (for example interdependencies between ecological communities and habitats can facilitate complex ripple effects flowing on from an initial disturbance of one ecological component) (E)
Unknown impact pathways (E)
Prediction of future effects
Uncertain future temperature and sea levels, and vegetation impacts due to climate change (P)
Uncertain future doses from long-lived radionuclides, to uncertain future receptor populations (P)
Episodic events
Uncertain probability of a major reactor accident, which is due to a scarcity of data on previous incidents or component failure (P)
Uncertain receptor or environment conditions at time of episodic events (P)
Variability
Uncertain exposure to radioactivity from a major reactor accident under variable prevailing winds and non-uniform receptor densities (P)
Top-down approaches ignoring site specificity [97,98][a] (M)
Limitation in depth and/or breadth, and spatial and temporal boundaries
Depth: the systematic error in all life-cycle inventories compiled using process analysis, which is caused by the truncation of the system by a finite boundary that usually includes upstream processes of only first or second order [43,99,100] (M)
Breadth: the omission of (M)
– processes leading to damage
– system components that during their production or operation cause impacts
– indicators or components thereof, e.g. the omission of ecosystem impacts ([48] p. 66), non-environmental impacts such as military spending for energy security [36], or cost of nuclear proliferation [57]
setting of spatial and temporal boundaries that are arbitrary[b], or inconsistent across methods and/or alternatives;
Double-counting
Unknown synergistic or cumulative effects of different pollutants, mix of technologies, or different indicators (E)
Overlap of use values with non-use values, if the latter are associated with unknown (because indirect or otherwise hidden) service flows from ecosystems to people (M, C)
VALUATION
Sensitivity of results to choices of discount rates in monetisation[c] (C)
Biases and inconsistencies occurring during elicitation of indicator weights: people may construct preferences while being interviewed, or may state preferences that contradict utility theory[d] (C)
Variability because opinions vary between people, and also change over time: results of valuation exercises can rarely be generalised, and are prone to criticism and dispute [101] (P)
Omission of non-use values, such as existence of pristine nature, bequests to future generations, or optional uses[e] (M)
Stochastic uncertainty resulting out of imperfect preference measurements[f] (P)

[a] Using fate and exposure modeling, Hertwich et al. [34] show that varying landscape characteristics causes less than 10% of total variability of potential doses from toxic emissions, but that the behaviour of the chemical in its release compartment, and exposure routes are the main uncertainty sources. Eyre [83] points out that site independence may be valid for high-stack emissions, but not necessarily for emissions from transport.

[b] For example 100,000 years for long-lived radionuclides ([43] p. 2), or 100-year time horizon for greenhouse gases [102].

[c] Varying the discount rate has substantial effects on damage cost. For the extreme example of impacts from radionuclides with half lives exceeding 100,000 years, choices are so sensitive that even very small discount rates lead to far-future damages being negligible.

[d] See the interesting literature on violations of classical utility theory by phenomena such as fanning-out, preference reversal and framing effects [103–105], extremeness aversion and contrast effects [106], as well as attempts to reconcile economic theory with evidence from psychology through ever-adapting new utility formulations [107,108].

[e] This argument can refer to diverging point of views [109,110], ie either that non-use values have not been considered adequately and should be fully evaluated using for example Contingent Valuation [111], that they cannot be reliably measured and therefore should not be considered [101], or that existence values should not be conflated with monetisation because they have nothing to do with benefits or welfare but with beliefs and rights [76,77].

[f] The European Commission ([48] p. 87) argues that "there is no sensible way of attaching probabilities to judgments, scenarios of the future, the 'correctness' of ethical choices or the chances of error", and that "there is no reason to expect that a statistical distribution has any meaning when attempting to take into account the possible variability in these parameters". On the other hand, if one accepts that 'willingness to pay' for example is amenable to measurement, preferences elicited from a respondent sample may range around a central value. For example, if the mean of 'morbidity cost' or 'utility loss from pain and suffering' across a whole population were the quantity sought in an externality study, statistical uncertainties may arise out of the respondent sample not representing this population. Another example for stochastic uncertainty within valuation is the value of a statistical life (VSL) or years-of-life-lost (YOLL), which may or not depend on a statistically uncertain age at death, or on health status [112,113].

causes (**Table 1**).[6] Some of these causes of uncertainty may be stochastic, that is parametric as a statistical distribution around a mean value. Other causes, for example in inadequate models or predictions of the future, may be systematic, that is yielding too high or too low values (unknown impact pathways being an example of the latter). Naturally, stochastic processes lend themselves to statistical analysis, and for the sake of simplicity, these will be the focus in this work. Note that systematic uncertainties due to unknown impact pathways may

[6] Hofstetter [20] classifies these into 'epistemological uncertainty' (systematic lack of knowledge about nature and the future), 'subjectivity' (value judgments), and 'technical and methodological uncertainty' (statistical variation of parameters). Huijbregts [21] distinguishes parameter, model, and choice uncertainty, and also treats unknown spatial and temporal variability separately from uncertainty.

be potentially large[7], so that uncertainty figures given in the following likely represent lower bounds.

Along with the number of assumptions and pathways, the uncertainty in impact or externality assessments increases for subsequent modeling stages towards the endpoint.[8] Take for example the 'problem areas' of the ExternE study: climate change and radioactive exposure (see Fig. 1): While emissions of greenhouse gases are relatively well known, the estimates of climate change and associated impacts vary much more. Typical uncertainties of emissions figures are about 10% for energy-related CO_2, but higher for other greenhouse gases and other sources, such as 50%–100% for CH_4 from agriculture or CO_2 from land use changes [26].[9] On the far end of the pathway, estimates of economic damages from climate change commonly vary at least by a factor of two, sometimes by more than one magnitude [29–33]. The same holds for the radioactivity pathway: releases (at least those during normal plant operation) are better understood than exposure, doses, and incidents. A similar spread of uncertainty can be observed for other impact pathways, for example potential doses from toxic emissions [34], or fatalities resulting from occupational and accidental health risks [35].

Given the numerous sources of uncertainty and variability, it is not surprising that studies of comparatively similar energy technologies come up with significantly different external cost values [36–39]. Using multivariate regression, Sundqvist [40] shows that the variability in electricity externality estimates caused by methodological and scope discrepancies is comparable to that due to fuel types as different as coal and solar, and that site specificity has a minor influence. Even within the same study (ExternE) on a particular technology, estimates have changed significantly over time [16]. As to be expected, diverging or changing numbers may lead to contradictions, and generally erode the credibility of such assessments. Consequently, in the ExternE study, improvements regarding uncertainty are amongst the main recommendations for future research.

2 How Uncertainty Affects Endpoint Decision-making: Statistical Hypothesis Testing

In the ExternE study, uncertainty is expressed as the standard deviations Δe (or the 67%-confidence interval) of lognormally distributed damage cost e around their geometric mean $\bar{e}$ ([41]. Presumably, unknown systematic errors due to the truncations in depth and breadth, or due to lack of knowledge are not considered.[10] The standard deviations are estimated (by error propagation) to be in excess of ±1 order of magnitude ([43] p. 310; [44] pp. xviii-xxi).

Assuming two energy supply alternatives with two impacts pathways proceeding along mutually exclusive pathways, this estimate implies that their damage cost have to differ by at least one order of magnitude in order to be distinguishable statistically. More precise: Assuming a confidence interval of 67% = $^2/_3$, then only if nominal damage cost differ by more than one order of magnitude, the probability of mistakenly distinguishing the two alternatives while in reality they perform equally is less than (1–67%) = $^1/_3$. In statistics parlance, this is expressed as a so-called 'type-I error': the probability that the null hypothesis (H_0: $\bar{e}_1 = \bar{e}_2$) is rejected but true. In scientific hypothesis testing, a 95%-or-higher confidence level is usually chosen, with corresponding type-I error probabilities of 5% and lower required. Under these conditions, the damage cost of two alternatives have to differ by at least 1.96 ≈ 2 orders of magnitude in order to be distinguishable.[11]

Consider the following example: In the ExternE assessment of nuclear and wind power, the only common impact pathways are accidents. These impact pathways are mutually exclusive, since the accident causes in the two cases are completely unrelated. Externality cost values given are $\bar{e}_{\text{nucl}} = 0.1$ ECU/GWh, and $\bar{e}_{\text{wind}} = 0.22$ ECU/GWh.[12] Because of errors being lognormally distributed, one can subject the hypothesis of $\left|\log(\bar{e}_{\text{nucl}}) - \log(\bar{e}_{\text{wind}})\right|$ being null to a t-test, by comparing

[7] Shlyakter [22] offers a quantitative analysis of unsuspected errors revealed by increased knowledge over time: Examining empirical time series of measurements, this author concludes that uncertainties are often underestimated, and that exponential distribution functions are able to incorporate potential future unsuspected errors, based on past overconfidence (see also [23]).

[8] This principle is well-recognised in the literature: Udo de Haes ([9] p. 4) state that "in general, definition of an indicator closer to the environmental interventions will result in more certain modelling, but will render the indicator less environmentally relevant". Rosa et al. ([24] p. 1506) note that "there is a trade-off among indicators. On the one hand, the indicator should be as close as possible to the actual impacts [of climate change], i.e. damages. On the other hand, it should be calculated with certainty and therefore at the beginning of the cause-effect chain". Jolliet et al. [25] paraphrase this situation as "a dilemma between certainty and completeness".

[9] Uncertainties in greenhouse gas inventories, and especially in trends, affect verification of projects under the Clean Development Mechanism and Joint Implementation, as well as compliance with the Kyoto Protocol, and emissions trading [27,28].

[10] Due to limitations in depth and breadth, ExternE estimates have been described as 'sub-totals' ([42] p. 181).

[11] This argument needs qualification: Rabl and Spadaro ([41] p. 44) state that "it is instructive to distinguish between policy decisions that are binary (e.g., the choice between nuclear or coal-fired power plant) or continuous (e.g., what limit to set for the SO_2 emissions from a power plant)." They argue that "for binary decisions, the situation is sometimes simple because the uncertainty, even if large, has no effect if it doesn't change the ranking." In my view, this argument only holds if the same impact pathway is appraised for both alternatives: For example, if a gas-fired plant emits less greenhouse gases than a coal-fired plant, then its impact on climate change will be lower, no matter the uncertainties for determining climate change impacts. However, when comparing the radiological impact pathway of a nuclear plant with the climate change impact pathway of a wind plant, uncertainties are completely uncorrelated, so that – purely stochastically – the true radiological impact value may be below the mean, while the true climate impact value might be above the mean; hence, any ranking will be affected by uncertainty. In the same paragraph, Rabl and Spadaro [41] also say that "furthermore, the external cost of nuclear are so much lower than those of coal that the ranking is not affected by the uncertainties". This corresponds to the situation described above of two alternatives scoring so differently that they are distinguishable, even under large uncertainty. A similar but only qualitative argument was made by Hertwich et al. ([45] p. 270). The concept of overlapping distributions is also exploited in the theory of fuzzy sets [46, 47], and the overlap of the distributions in Fig. 1 corresponds to the intersection of fuzzy sets.

[12] ECU = European Currency Unit, GWh = Gigawatt-hour = 10^9 Watt-hours. External cost for the wind fuel cycle were calculated from average occupational accident cost (0.13 ECU/GWh) and public accident cost (0.09 ECU/GWh). External cost for the nuclear cycle are the consequence of radiological doses.

$\varepsilon = |\log(\bar{e}_{\rm nucl}) - \log(\bar{e}_{\rm wind})| \big/ \sqrt{\Delta(\log e_{\rm nucl})^2 + \Delta(\log e_{\rm wind})^2}$ to the inverse of the t-distribution. Inserting $\Delta(\log e_{\rm nucl}) = \Delta(\log e_{\rm wind}) = 1$, $\varepsilon = 0.24$. Assuming that the means $\bar{e}_{\rm nucl}$ and $\bar{e}_{\rm wind}$ were determined from a large sample, and applying the t-statistic for arbitrarily large degrees of freedom, $t_{\alpha/2} = \varepsilon$ for $\alpha = 0.81$. Hence the type-I error probability of mistakenly favouring one alternative when in reality they are indistinguishable is as high as 81%. This example may explain why one ExternE report states that "the best estimate of any damages value is therefore, on its own, inadequate for most policy making purposes" ([48] p. 87).

This situation of uncertain and therefore indistinguishable endpoint measures is likely to arise, especially in the case of complex environmental and social impacts. Decision-making may only be possible when alternatives exhibit considerably different scores, but in these cases the decision is likely to be so obvious that a sophisticated analysis would seem out of place. For example, Krewitt ([16] p. 842) states that "in spite of the existing uncertainties ExternE results were quite robust with regard to the relative ranking of different electricity generation technologies". However, this finding refers to a comparison of sources as different as coal, lignite, gas, nuclear and wind, with lignite and coal performing up to one order of magnitude worse than the remainder. Lignite and coal show a ranking reversal, and gas and nuclear are probably statistically indistinguishable. In this case it could be argued that one does not require the amount of research expended for ExternE to conclude that wind causes lower impacts than coal.

3 Midpoint Decision-making and Uncertainty: Applying Multi-criteria Methods

Facing prohibitively high endpoint uncertainty, one could revert to a midpoint level where indicators are sufficiently certain[13], and use multi-criteria decision (MCD) methods that make subjective trade-offs between midpoint categories explicit[14]. In Appendix A (online edition only, see http://dx.doi.org/10.1065/lca2005.04.201), an uncertainty calculus is developed for applying a MCD method to midpoint levels of ExternE impact pathways for two electricity generation alternatives. In this case the Analytic Hierarchy Process (AHP) is used[15], but the procedure is equally applicable for other MCD techniques. In the following, the AHP will be applied to an example decision derived from the ExternE study.

3.1 A simplified example

In the following, two electricity supply alternatives investigated in the ExternE study will be subjected to the AHP: nuclear and wind energy. For both alternatives, only two priority pathways will be considered: a) cancers from (mainly global, long-term, low-level collective C-14) radiological doses, and b) climate change impacts from fuel-combustion-related CO_2. Note that the examples given below represent an extremely simplified picture of the outcome of the ExternE study, for example in the way that the pathways were assumed to be linear, with constant conversion factors f_i. While the magnitude of the impact values e corresponds to the ExternE values, some of the midpoint impacts and uncertainties are based on other studies.[16]

The nuclear priority pathway (**Table 2**, compare Fig. 1) starts with releases of radioactivity during normal operation and as a consequence of accidents. Multiplication by conversion factors f_i leads to mid- and endpoints, and associated impacts e (ranges given in brackets). The uncertainties are expressed in logarithmic terms, that is $\Delta(\log e) = 1$ denotes an uncertainty of one order of magnitude.

[13] The debate around the midpoint/endpoint nexus has been especially prominent in the LCA literature [49]: While the SETAC [50] and the UNEP Life Cycle Initiative [25] approaches stop quantitative modeling relatively early in the cause-effect chain in order to limit uncertainties, the Eco-Indicator [3] and the Japanese National LCA project [51] try to enhance the relevance of the results by indicating damages through endpoint weighting. Comparing mid- and endpoint approaches is also the subject of the ReCiPe project funded by the Dutch government [52]. While the ReCiPe project advocates the use of sensitivity analysis, and certain scenarios, archetypal attitudes or 'world views', it explicitly does not deal with error propagation and statistical analysis for decision-making.

[14] For a discussion of the role of MCD tools within LCA see [53–55]. Noh et al. [56] compare three MCD methods applied in LCA. MCD tools were also suggested in an ExternE newsletter [57] for dealing with non-environmental externalities such as from nuclear proliferation risks.

[15] The AHP has been criticised for shortcomings such as rank reversal, its lack of reference points, and the independence of weights from attribute ranges [58,59]. Since these are problems that are unrelated to the topic of this article, they shall not be dealt with here.

[16] The author is also aware of and agrees with Rabl et al.'s ([41] p. 44) warning that providing definite values for uncertainties implies "a false sense of precision, unjustified in view of the need to use subjective judgment to compensate the lack of information about sources of uncertainties and probability distributions". Furthermore, it may not always be possible to find a range for impact pathway parameters, let alone a probability distribution. Therefore, uncertainty may be better conveyed by descriptive labels such as 'high', 'medium' and 'low' confidence, and/or by applying fuzzy set methods [47,60,61].

Table 2: Simplified impact pathway for radiological impacts of nuclear power (after [43]). All values are normalised to 1 TWh of electrical output

Pathway stage / Conversion	Impact e	Range	Unit	$\Delta(\log e)$
Radioactivity release / f_3 = 0.01 GBq/GBq	91.5	(61–137)	GBq / TWh	0.18
Exposure / f_5 = 14.2 man.Sv/GBq	0.92	(0.4–2.3)	GBq / TWh	0.40
Dose / f_7 = 0.17 inc./man.Sv	13.0	(2.3–72.7)	man. Sv / TWh	0.75
Cancer / f_9 = 158 ECU_{disc}/inc.	2.21	(0.3–14.5)	inc. / TWh	0.82
Externality cost	350	(48–2,544)	ECU_{disc} / TWh	0.86

Notes: GBq = Gigabequerel = 10^9 decays/second; TWh = Terawatt-hour = 10^{12} Watt-hours; man.Sv = man-Sievert is a unit for the average individual radiological dose equivalents; inc. = incidents; ECU = European Currency Unit is the monetary unit used in the ExternE study; disc = discounted. The $\Delta(\log e)$ were calculated from geometric standard deviations given by [41])

Table 3: Simplified impact pathway for climate change impacts of wind power (partly after [44], and [24]). All values are normalised to 1 TWh of electrical output

Pathway stage / Conversion	Impact *e*	Range	Unit	Δ(log *e*)
GHG emissions / $f_4 = 0.48\ 10^{-9}$ ppm/T CO_2	9.1	(8–11)	t CO_2 / TWh	0.08
GHG concentration / $f_6 = 3.48$ t C yr/ppm	4.4	(3–6)	10^{-9} ppm / TWh	0.13
Global warming / $f_8 = 49.17$ ECU/t C yr	153	(62–374)	t C yr /TWh	0.39
Climate change / $f_{10} = 0.2$ ECU_{disc}/ECU	7,500	(1,382–40,689)	ECU /TWh	0.73
Externality cost	1,500	(240–9,375)	ECU_{disc} / TWh	0.80

Notes: GHG = greenhouse gas; t = tonnes; TWh = Terawatt-hour = 10^{12} Watt-hours; ppm = parts per million; t C yr = tonne-years of carbon is a measure of cumulative global warming ([24]); ECU = European Currency Unit is the monetary unit used in the ExternE study; disc = discounted

For the nuclear impact pathway it is assumed here that humans are exposed to f_3 = 1% of the released radioactivity. For inhalation and ingestion of C-14, the dose conversion is $f_3 \times f_5$ = 0.142 man.Sv/GBq, integrated over 100,000 years ([43] p. 50). Determining f_3 involves Gaussian plume, trajectory, and deposition modeling. In the simplified dose-response relationship f_7, fatal and non-fatal cancers were counted, but not hereditary effects. Systematic errors, for example due to choosing the wrong type of relationship, are not accounted for ([41] p. 41). The final externality cost of 350 ECU_{disc}/TWh are the logarithmic mean between the extremes of 50 and 2500 ECU_{disc}/TWh calculated for 0% and 10% discount rates ([43] p. 200). Midpoint uncertainties were taken from [41] Table 3.[17] Note that considering the near-impossibility of estimating parameters and impacts for thousands of years into the future, the above enumeration may well be meaningless [16].

The wind alternative's priority impact pathway (**Table 3**) deals with greenhouse gases emitted during the plant operation as well as embodied in the turbine infrastructure. Systematic errors due to the truncation of the system boundary [64] are not taken into account. The climate change impact pathway can be expressed in many different ways; however, the way given here suffices to provide an example for multi-criteria decision-making under uncertainty. The increase of atmospheric greenhouse gas concentrations is simplified as a multiple of cumulative emissions (compare [36] p. 426). Global warming impacts are expressed as temporally integrated atmospheric concentrations ([24] p. 10). Climate change impacts are manifold, involving a range of midpoints with varying units, of which undiscounted cost were chosen here. Discounting over several centuries (as is necessary for climate change impacts) typically involves a cost reduction of a factor 5–10, leading to the final estimate from the ExternE study ([43] p. 118). Emissions are assumed to be known with 10–20% uncertainty[18] ([26]). Concentration and global warming uncertainty were taken from trajectories given in the third assessment report of the Intergovernmental Panel on Climate Change (IPCC, [65]). The geometric standard deviation of external costs is σ_g = 2.5 ([41] p. 42), so that $\Delta(\log e) = \log\sqrt{\sigma_g} = 0.80$. The uncertainty of climate change impacts was derived by subtracting valuation- and discounting-related uncertainties (given in [41] Table 3) from external cost uncertainties. It is important to keep in mind that ExternE as well as IPCC sources state that ranges of damage cost are not based on a comprehensive scientific uncertainty appraisal and at best incomplete, and that strictly speaking, no central figure can be endorsed as a most likely estimate ([48] p. 63).

3.2 Applying the AHP

In order to illustrate uncertainty trade-offs, a relatively certain indicator ('jobs') is added to the more uncertain indicators 'cancer' and 'climate'; let these three indicators represent societal goals. As a first step, a decision-maker may be asked to specify a required maximum uncertainty level, say a maximum type-I-error probability of 0.33. Second, based on pairwise comparisons of preferences, AHP weights are elicited.[19] Eqs. 1 to 6 in Appendix A (online edition only, see http://dx.doi.org/10.1065/lca2005.04.201.1) can then be applied to performances P_{ij} of the alternatives j in terms of indicators i, in order to obtain normalised performances $p_{ij} = P_{ij}^{\beta_i} / \Sigma_i P_{ik}^{\beta_i}$, scores $s_j = \Sigma_i w_i p_{ij}$, and uncertainties $\Delta(\ln s_j)$.

The result of the AHP process shows that when evaluated at endpoints, wind power scores slightly higher (that is better) than nuclear power (**Table 4**). However, the *t*-test (rightmost columns) shows that the type-I error probability of the overall score is so high (0.53) that the decision-maker's requirement is not met: a decision under these circumstances is virtually impossible. Moreover, quoting an endpoint result in this case may only distract from the existing prohibitive uncertainty (compare [70] p. 214). Note that the employment indicator alone allows a clear distinction, however when determining the aggregate score this certainty is swamped by the more uncertain indicators.

[17] It has been recognised that the externality cost calculated in the above fashion do not reflect society's willingness to pay to avoid a nuclear accident, and that not only expert opinion and engineering calculus (as in [35]), but also the public's aversion of (voluntarily incurred or imposed) risk should influence the probability distributions [48,62]. For example, damage measures perceived by people at risk are likely to exceed those expected by engineers based on probability and likely cost [10,63], and large-impact low-probability risks are less tolerated because the magnitude of the potential damage exceeds funds or capacities ([37] p. 522). This type of externality is not implemented in ExternE, and will therefore not be considered at this stage, but in the discussion.

[18] $\Delta(\log e) = \log e_{max} - \log \bar{e} = \log \frac{e_{max}}{\bar{e}} = \log \frac{\bar{e}(1+20\%)}{\bar{e}} = \log 1.2 = 0.08$

[19] Note that in this case, the common AHP practice of eliciting weights independently of attribute ranges is applied. However, it has been argued that under certain conditions judgments are actually range-sensitive [58,66–69].

Table 4: Decision-making near endpoints, at midpoints, and at intervention levels. Uncertainties are expressed as orders of magnitude. Units for greenhouse gas and radioactivity pathways as in Table 2 and 3, 'jobs' in arbitrary units

Level	Indicator	Performance		Relative performance		x AHP	Score		t	type-I
		Nuclear	Wind	Nuclear	Wind	weights =	Nuclear	Wind		error prob
near endpoint	Jobs	100 ± 0.04	60 ± 0.04	0.63 ± 0.02	0.38 ± 0.04	0.2	0.13 ± 0.02	0.08 ± 0.04	5.20	0.00
	Cancer	2.21 ± 0.82	0.22± 0.82	0.09 ± 1.05	0.91 ± 0.11	0.5	0.05 ± 1.05	0.45 ± 0.11	0.95	0.34
	Climate change	750 ± 0.73	7500 ± 0.73	0.91 ± 0.09	0.09 ± 0.94	0.3	0.27 ± 0.09	0.03 ± 0.94	1.05	0.29
						Totals	**0.44 ± 0.12**	**0.56 ± 0.10**	**0.63**	**0.53**
mid-point	Jobs	100 ± 0.04	60 ± 0.04	0.63 ± 0.02	0.38 ± 0.04	0.2	0.13 ± 0.02	0.08 ± 0.04	5.20	0.00
	Dose	13.0 ± 0.75	1.3 ± 0.75	0.09 ± 0.96	0.91 ± 0.10	0.5	0.05 ± 0.96	0.45 ± 0.10	1.04	0.30
	Global warming	15.3 ± 0.39	152.5 ± 0.39	0.91 ± 0.05	0.09 ± 0.50	0.3	0.27 ± 0.05	0.03 ± 0.50	1.99	0.05
						Totals	**0.44 ± 0.10**	**0.56 ± 0.08**	**0.75**	**0.45**
inter-vention	Jobs	100 ± 0.04	60 ± 0.04	0.63 ± 0.02	0.38 ± 0.04	0.2	0.13 ± 0.02	0.08 ± 0.04	5.20	0.00
	Exposure	0.92 ± 0.40	0.09 ± 0.40	0.09 ± 0.51	0.91 ± 0.05	0.5	0.05 ± 0.51	0.45 ± 0.05	1.94	0.05
	GHG concentration	0.44 ± 0.13	4.38 ± 0.13	0.91 ± 0.02	0.09 ± 0.16	0.3	0.27 ± 0.02	0.03 ± 0.16	6.06	0.00
						Totals	**0.44 ± 0.05**	**0.56 ± 0.04**	**1.44**	**0.15**

In order to reduce the type-I error probability to below 0.33, the decision could be located closer to the interventions levels, for example using the indicators 'dose' and 'warming', or 'exposure' and 'concentration' instead of 'cancer' and 'climate'. Note that relative performances and scores are now associated with lower uncertainties. As a result of the simplified linearisation of the impact pathway (see Table 2 and 3), wind power still scores better, but in practice this need not be the case. The main point is that a choice between nuclear and wind is more certain at only 0.45 and 0.15 type-I error probabilities, respectively. Basically, the decision-maker has given up the objectives 'cancer' and 'climate', because of a clear lack of knowledge and understanding, even though these objectives might have matched more closely the societal goals. The new objectives are to reduce exposures and concentrations, and their only remaining link to the societal goals is that they are known to be positively related. The decision-maker's shift to this new set of objectives makes perfect sense, since the uncertainty of the old objectives precluded any decision.

3.3 Relevance

In spite of their increased certainty, it has been argued that indicators at the intervention or midpoint level are only 'proxy attributes' ([71] p. 112), and carry 'a hidden uncertainty in their [environmental] relevance' ([9] p. 8), and that choosing indicators closer to interventions levels only moves the uncertainty from the numbers to the (environmental) relevance. This comes about because important factors in the cause-effect chain of the impact pathway might be left out of the midpoint information, or because weights may be more uncertain at midpoints than at endpoints.

In order to allow the decision-maker to address the more tangible and relevant endpoint question, even though affected by systematic epistemological uncertainty, Keeney et al. ([72]; as cited in [71]) suggest replacing midpoint impacts p_{ij} with decision-makers' midpoint utility $u_{ij}(p_{ij}) = \int u_{ij}(D_{ij})\ \mathrm{prob}(D_{ij}|p_{ij})\ \mathrm{d}p_{ij}$, where D_{ij} are endpoint damages of midpoint impacts p_{ij}, $u_{ij}(D_{ij})$ the decision-maker's utility function for endpoint damages, and $\mathrm{prob}(D_{ij}|p_{ij})$ is the conditional probability of D_{ij} occurring as as result of p_{ij}. Scoring then proceeds as usual via $s_j = \Sigma_i\, w_i\, u_{ij}(p_{ij})$. Acknowledging that a comprehensive enumeration of endpoint damages is impossible, the idea is basically to use an elicitable utility function $u_{ij}(p_{ij})$ in place of the unknown final part of the impact pathway $D_{ij} = f(p_{ij})$. However, this formulation still faces the difficulty of having to enumerate $\mathrm{prob}(D_{ij}|p_{ij})$, and relevant information is once again highly uncertain.[20]

The certainty-relevance trade-off seems in fact pivotal in the midpoint/endpoint debate in LCA [45,49]: In order to answer one endpoint question, uncertain endpoint damages may tell as little as more certain but less relevant midpoint numbers. The following Section discusses further advantages and disadvantages of mid- and endpoints and, notwithstanding the seemingly inevitable certainty/relevance trade-off, gives some arguments in favour of multi-criteria decision-making at midpoints.

4 Discussion

4.1 Midpoints or endpoints?

With respect to whether mid- or endpoint indicators are favourable, Heijungs et al. [52] elaborate: "Many claim that endpoint indicators are easier to understand and thus interpret, as they express issues of societal concern, such as human health damage or ecosystem quality damage. This means that the uncertainty in the interpretation can be potentially lower compared to a midpoint method, especially in decision-making. Others claim, however, that midpoint indicators are easier to understand and thus interpret, as they relate to facts and phenomena, such as decrease of the ozone layer, whereas endpoint indicators pertain to badly-defined and subjective intuitive notions, such as human health".

[20] Considering the complexity of the midpoint-endpoint chain, Rahimi et al. [61] use linguistic fuzzy variables that allow for vagueness about endpoint damages.

In my view, decision-making at midpoints has several advantages:[21] First, instead of providing a few aggregated numbers, the more multi-facetted midpoint information clearly reveals the multi-dimensionality of the problem at hand, and the trade-offs between the inherent aspects. Appropriately chosen MCD methods can aid the decision-maker if the amount of information exceeds cognitive limits. Second, compared to midpoints, endpoint assessments require additional steps of data collection, modeling and computation, and hence require more time, labour and resources, with potentially little gain in decision certainty. Third, as highlighted by the example of the employment indicator in Table 4, aggregation of impact categories and pathways may cause uncertain components to swamp certain components. In contrast, reverting to midpoint levels opens the opportunity of carrying out an iterative procedure, where too uncertain indicators are simply excluded. Consider again Table 4 and assume that the decision-maker insists on near-endpoint indicators: Given that with regard to 'cancer' and 'climate change', the two alternatives are indistinguishable within the certainty required, a decision could sensibly be based on 'jobs' alone, because in terms of this criterion at least a difference can be discerned.

Fourth, and maybe most importantly, multi-criteria decision analysis at midpoint levels is able to include characteristics that impact modeling and valuation has trouble quantifying. The decision-making literature offers a rich repertoire of factors that significantly influence people's decisions, but are difficult or impossible to quantify. Stirling ([37] p. 518) provides an extensive list of problems faced by externality assessments that "might be summed up as 'a failure to address the multidimensional nature of environmental appraisal'".[22] In addition to the uncertainty aspects that are the topic of this article, Stirling and others [45,75–77] find that aggregate external cost estimates lack representation of

– the spatial, social and temporal distribution of impacts, burdens and benefits (international, inter-generational and inter-societal equity);
– the autonomy of the people affected (voluntariness, controllability and familiarity of exposure);[23]
– perceptions of severity, frequency, immediacy and reversibility of potential impacts;[24]
– perceived risk (as opposed to calculated risk based on engineers' expectations of magnitudes and probabilities);[25]
– ethical, moral, religious and political beliefs and principles;
– perceived incompleteness of human knowledge.

For example, facing a choice between nuclear and wind power where damages are indistinguishable and impact pathways complex, decision makers may actually consider those aspects they know and that distinguish the alternatives. For example, in Australia, radioactivity evokes images of contaminated rivers in Jabiluka (a Uranium mine in Kakadu National Park) and sick animals and people, while greenhouse gas emissions spell droughts, storms and bleaching corals. None of these associations are true endpoint measures. One could argue that when ranking the relative importance of nuclear versus wind power, respondents may actually think of prominent but proxy midpoint impacts when passing their judgment [79], and not complete impact pathways or damage costs. They will likely judge the alternatives with respect to voluntariness, severity, immediacy etc. For example, people may prefer the relatively certain prospect of struggling in a warmer world to the small possibility of being struck by a radiological cancer leading to a gruesome death. Or, they may not trust the authorities administering nuclear power in guaranteeing safe operation or prevention of proliferation. Or, they may think of dumping radioactive waste on future generations for unimaginable times to come violates an ethical principle that has no trade-offs. These and many other thoughts may actually be quite clearly formed and certain, leading respondents to weight 'radioactivity' as more important than 'greenhouse gas emissions'. Note that in order to judge many of the above aspects, people do not need extensive knowledge about impact pathways and damage cost.

4.2 How uncertainty affects the choice of MCD method: Range-sensitivity of weights

Uncertainty bears not only on choices between mid- and endpoints, but also on choices between MCD methods. Some authors maintain that the elicitation of weights using questions that purely relate to attributes without any reference to ranges (such as in the AHP and Table 4) are meaningless, and that preferences depend on the available ranges [58,68]. For example, in order to answer the question 'What is more important in a car: cost or colour?', one would want to know how expensive and colourful the cars are that can be chosen from. One would expect that for many people cost is more important in a purchase decision. However, if all cars cost about the same (small range), but had vastly different colours (large range), then a choice would be made on colour.

However, for attributes such as climate change or cancer, where endpoint ranges are extremely broad, and midpoint ranges (emissions and releases) are difficult to interpret, respondents may actually weight attributes independent of ranges, that is they switch from preferences within the narrow range and context of alternatives to what Fischer [69] calls generalised notions about attributes and range-inde-

[21] Without going into numerical and methodological details, Udo de Haes [73] comes to some of the above conclusions when recommending social panels evaluating midpoints as the preferred approach for weighting in LCA. He also qualifies the finding by pointing out that the decision may be affected by who is a panel member, and where and when the decision is made.

[22] See also a paper by Watson [74] on the different origins of monetisation (as in cost-benefit analysis) and decision-analytical tools in economics and psychology, respectively.

[23] Examples: voluntariness – worker versus general public, controllability – risks from car travel versus risks from living near a power plant, familiarity – expert's versus lay person's knowledge.

[24] Examples: severity and frequency – reactor accident versus car accidents, immediacy – air pollution and immediate respiratory diseases versus delayed climate change, reversibility – noise versus species loss.

[25] Freeman [78] makes the point that it is common and accepted to base investment decisions under uncertainty on *ex-ante* criteria such as risk aversion.

pendent, 'global' preferences, with a maximum spectrum of situations in mind.[26]

Range-sensitivity or insensitivity of weights bears on the choice of multi-criteria decision method: Interpreting the weighted sum $s_j = \Sigma_i\ w_i\ p_{ij}$ as a utility function imposes a specific utility trade-off interpretation on the weights w_i, placing them in the context of the attribute ranges of alternatives [66,67,69]. This means that, in utility-based methods, weights cannot be elicited independently from attribute ranges. In contrast, AHP performances $p_{ij} = P_{ij}^{\beta_i} / \Sigma_i\ P_{ik}^{\beta_i}$ cannot be interpreted as cardinal utilities, and the weights are chosen independently from performance ranges ([67] p. 574).

Considering that the AHP is said to be particularly suited to deal with intangibles that do not lend themselves for easy translation into utility terms [81], and that are vague and uncertain, global preferences are likely to occur. These global preferences (or Fischer's generalised notions) may refer to the beliefs, principles, rights and feelings listed in the previous section, and may therefore be 1) independent of ranges, and 2) independent of mid- or endpoints. Given 1), the AHP's unreferenced ratio-scale approach may not be so inappropriate as critics of the AHP's lack of meaningful reference intervals [58,59,68,82] purport. Given 2), midpoint weights and endpoint weights based on global preferences may actually be identical, as in Table 3 (compare [79] p. 210).

5 Conclusions

Applying statistical hypothesis testing to the example of impact pathways in the ExternE study on external cost of electricity supply alternatives, this article has quantitatively shown that impact and external cost assessments featuring a single, aggregated endpoint measure can be so uncertain that neither cardinal differences between, nor ordinal rankings of alternatives retain sufficient significance while moving along the impact pathway. As a result, as Eyre [83] states, "it seems an inescapable conclusion that, for some important impacts, reliable monetary valuations are not a realistic objective". For example, even though expected damages from climate change often dominate impact and cost rankings, they may only be 'considered as a helpful indicator of environmental problems rather than an input into cost-benefit analysis' [42].

Moreover, presented as discrete values, figures for endpoint damage cost, and differences between alternatives can be deceptive if seen without a clear understanding of the uncertainties involved. In this respect, ExternE authors state that "there is a need for other users of the results [...] to both understand and pass on information regarding uncertainty, and not to ignore it because of the problems that inevitably arise. The Project team feels so strongly about this that reference should not be made to the ExternE Project results unless reference is also made to the uncertainties inherent in any analysis and our attempts to address them" ([48] p. 63).

Notwithstanding it falling short of its ambitious objective, the endpoint modeling in the ExternE project has demonstrated that external cost of some electricity generation alternatives can be potentially large. The associated high uncertainties can be a valuable result in themselves, because they convey a risk that, seen in the context of the precautionary principle, can stimulate action towards implementing clearly sustainable technologies as a means of hedging against the worst scenarios [83]. Finally, endpoint and impact pathway knowledge can aid weight elicitation at the midpoint level.

Still, for the purpose of decision-making, it may not make sense to expend resources on shedding light on endpoint parts of impact pathways, when uncertainty in further midpoint factors is already prohibitive. As Krupnick et al. ([36] p. 428) put it: "The weakest link in the sequence of functions in a pathway sets the standard for the level of detail in the analysis. Consequently there may be little benefit from a high degree of resolution at one stage that is only lost in the final analysis because of less resolution at another stage."

If endpoints are too uncertain to allow a decision to be made with reasonable confidence, an assessment could be shifted to midpoint levels. Here however, it is often pointed out that the multi-facetted midpoint information is too complex and poses difficulties for decision-makers. Moreover, midpoint indicators are generally further removed from people's experience, and less relevant to the question that people actually want to solve. There is an uncertainty associated with this diminished relevance which may well equal endpoint uncertainty.

In this paper it has been argued that if the endpoint question is unanswerable (with the certainty required by the decision-maker), a decision should be made on the basis of stakeholders' subjective judgments about the more certain midpoint levels. This is because in addition to quantitative data, there is a wealth of reasons that affect decisions, which are based on beliefs, principles, rights and feelings. Many people would have relatively clear and certain preferences with respect to these beliefs etc, and would insist that these are valid reasons that should play a role in decisions. Since it is exactly these aspects that endpoint approaches such as impact pathway modeling and monetisation are largely unable to deal with, multi-criteria approaches applied to midpoints appear as the preferred option. A conclusion could be summarised as: When bridging the midpoint-endpoint gap, the difference between using impact pathway modeling and monetisation, or using human judgment is often the same as that between going by a wild guess or by gut feeling. Depending on how wild that guess is, people may actually be happier with gut feeling.

Acknowledgements. This work was carried out in the scope of a Visiting Professorship at the Institute of Environmental Studies of the Graduate School of Frontier Sciences at the University of Tokyo. The author is grateful to Prof Ryuji Matsuhashi for supporting the application and the author's tenure, and to the Japan Society for the Promotion of Science for financial funding. The author also wishes to thank Helias Udo de Haes for good advice, and Paul Cohen of University of Sydney Library for help with obtaining literature.

[26] Fischer et al. [79] observe a bias in respondents weighting proxy attributes rather than endpoints. This bias will in general depend on whether the endpoint range expected from the proxies lies within the lower or upper part of the respective globally perceived (for example maximum possible) endpoint range. Hammitt [80] shows that climate change abatement policy outcomes may be affected by whether mid- or endpoints are evaluated.

References

[1] Narodoslawsky M, Krotschek C (1995): The sustainable process index (SPI): evaluating processes according to their environmental capability. Journal of Hazardous Materials 41 (2–3) 383–397

[2] Rees WE (1992): Ecological footprints and appropriated carrying capacity: what urban economics leaves out. Environment and Urbanization 4 (2) 121–130

[3] Goedkoop M, Hofstetter P, Müller-Wenk R, Spriemsma R (1998): The Eco-Indicator 1998 explained. International Journal of Life-Cycle Assessment 3 (6) 352–360

[4] Pennington DW, Potting J, Finnveden G, Lindeijer E, Jolliet O, Rydberg T, Rebitzer G (2004): Life cycle assessment part 2: current impact assessment practice. Environment International 30, 721–739

[5] Hertwich EG, Pease WS, Koshland CP (1997): Evaluating the environmental impact of products and production processes: a comparison of six methods. Science of the Total Environment 196, 13–29

[6] Notarnicola B, Huppes G, van den Berg NW (1998): Evaluation options in LCA: the emergence of conflicting paradigms for impact assessment and evaluation. International Journal of Life Cycle Assessment 3 (5) 289–300

[7] Dreyer LC, Niemann AL, Hauschild M (2003): Comparison of three different LCIA methods: EDIP97, CML2001 and Eco-indicator 99. International Journal of Life Cycle Assessment 8,191–200

[8] Bengtsson M, Steen B (2000): Weighting in LCA – approaches and applications. Environmental Progress 19 (2) 101–109

[9] Udo de Haes HA, Jolliet O, Finnveden G, Hauschild M, Krewitt W, Mueller-Wenk R (1999): Best available practice regarding impact categories and category indicators in life cycle impact assessment. International Journal of Life Cycle Assessment 4 (2) 1–15

[10] Freeman AM (1996): Estimating the environmental cost of electricity: an overview and review of the issues. Resource and Energy Economics 18, 347–362

[11] Haneman WM (1991): Willingness to pay and willingness to accept: how much can they differ? American Economic Review 81 (3) 635–647

[12] Kahneman D, Knetsch JL, Thaler RD (1991): The endowment effect, loss aversion, and status quo bias. Journal of Economic Perspectives 5 (1) 193–206

[13] Hofstetter P, Baumgartner T, Scholz RW (2000): Modelling the valuesphere and the ecosphere. International Journal of Life Cycle Assessment 5 (3) 161–175

[14] Itsubo N (2000): Screening life cycle impact assessment with weighting methodology based on simplified damage functions. International Journal of Life Cycle Assessment 5 (5) 273–280

[15] ETSU Energy Technology Support Unit (1995): Vol. 1: Summary. In: European Commission, editor. ExternE – Externalities of Energy. Luxembourg: European Commission, Directorate-General XII

[16] Krewitt W (2002): External cost of energy – do the answers match the questions? Looking back at 10 years of ExternE. Energy Policy 30 839–848

[17] Hertwich EG, Hammitt JK, Pease WS (2000): A theoretical foundation for life-cycle assessment. Recognizing the role of values in environmental decision making. Journal of Industrial Ecology 4 (1) 13–28

[18] Nunes PALD, Van den Bergh JCJM (2001): Economic valution of biodiversity: sense or nonsense? Ecological Economics 39, 203–222

[19] Turner RK, Paavola J, Cooper P, Farber S, Jessamy V, Georgiou S (2003): Valuing nature: lessons learned and future research directions. Ecological Economics 46, 493–510

[20] Hofstetter P (2000): The different levels of uncertainty assessment in LCIA. In: Bare JC, Udo de Haes HA, Pennington DW (eds), An international workshop of life cycle impact assessment sophistication. Cincinnati, USA: National Risk Management Research Laboratory, U.S. Environmental Protection Agency 38–40

[21] Huijbregts MAJ (1998): Application of uncertainty and variability in LCA. Part I: A general framework for the analysis of uncertainty and variability in life cycle assessment. International Journal of Life Cycle Assessment 3 (5) 273–280

[22] Shlyakter AL (1994): An improved framework for uncertainty analysis: accounting for unsuspected errors. Risk Analysis 14, 441–447

[23] Hammitt JK, Shlyakter AL (1999): The expected value of information and the probability of surprise. Risk Analysis 19 (1) 135–152

[24] Rosa LP, Ribeiro SK, Muylaert MS, de Campos CP (2004): Comments on the Brazilian Proposal and contributions to global temperature increase with different climate responses – CO_2 emissions due to fossil fuels, CO_2 emissions due to land use changes. Energy Policy 32 (13) 1499–1510

[25] Jolliet O, Brent A, Goedkoop MJ, Itsubo N, Mueller-Wenk R, Peña C, Schenk R, Stewart M, Weidema B (2003): Final Report of the LCIA Definition Study. Internet site <http://www.unepie.org/pc/sustain/reports/lcini/LCIA_defStudy_final3c.pdf>. Lausanne, Switzerland: Life Cycle Initiative, École Polytechnique Fédérale de Lausanne

[26] Subak S (1999): On evaluating accuracy of national methane inventories. Environmental Science & Policy 2, 229–240

[27] Rypdal K, Winiwarter W (2001): Uncertainties in greenhouse gas emission inventories – evaluation, comparability and implications. Environmental Science & Policy 4, 107–116

[28] Gupta J, Olsthoorn X, Rotenberg E (2003): The role of scientific uncertainty in compliance with the Kyoto Protocol to the Climate Change Convention. Environmental Science & Policy 6, 475–486

[29] Ghosh P (1993): Perspectives on climate change from economics: cost benefit analyss, models, inertia, and policy instruments. In: Achanta AN (ed), The Climate Change Agenda: An Indian Perspective. New Delhi, India: Tata Energy Research Institute, pp 275–298

[30] Fankhauser S (1995): Valuing climate change: an economic assessment of global warming impacts. In: Murai S (ed), Toward Global Planning of Sustainable Use of the Earth. Amsterdam, Netherlands, Elsevier, pp 167–188

[31] Tol RSJ (1996): The damage cost of climate change towards a dynamic representation. Ecological Economics 19, 67–90

[32] Pearce D (1999): Economic analysis of global environmental issues: global warming, stratospheric ozone and biodiversity. In: van den Bergh JCJM, editor. Handbook of Environmental and Resource Economics. Cheltenham, UK, Edward Elgar, pp 488–504

[33] Darwin RF, Tol RSJ (2001): Estimates of the economic effects of sea level rise. Environmental and Resource Economics 19, 113–129

[34] Hertwich EG, McKone TE, Pease WS (1999): Parameter uncertainty and variability in evaluative fate and exposure models. Risk Analysis 19 (6) 1193–1204

[35] Fritzsche A (1989): The health risks of energy production. Risk Analysis 9 (4) 565–577

[36] Krupnick AJ, Burtraw D (1996): The social cost of electricity - do the numbers add up? Resource and Energy Economics 18, 423–466

[37] Stirling A (1997): Limits to the value of external costs. Energy Policy 25 (5) 517–540

[38] Schleisner L (2000): Comparison of methodologies for externality assessment. Energy Policy 28, 1127–1136

[39] Schleisner L (1999): Differences in methodologies used for externality assessment – why are the numbers different? Risø-R-1126(EN). Roskilde, Denmark, Risø National Laboratory

[40] Sundqvist T (2004): What causes the disparity of electricity externality estimates? Energy Policy 32, 1753–1766

[41] Rabl A, Spadaro JV (1999): Damages and costs of air pollution: an analysis of uncertainties. Environment International 25 (1) 29–46

[42] Krewitt W, Heck T, Trukenmüller A, Friedrich R (1999): Environmental damage costs from fossil electricity generation in Germany and Europe. Energy Policy 27, 173–183

[43] EEE Eyre Energy Environment, ENCO Environmental Consultants (1995): Vol. 5: Nuclear. In: European Commission, editor. ExternE – Externalities of Energy. Luxembourg, European Commission, Directorate-General XII

[44] EEE Eyre Energy Environment, ENCO Environmental Consultants (1995): Vol. 6: Wind & Hydro. In: European Commission, editor. ExternE – Externalities of Energy. Luxembourg, European Commission, Directorate-General XII

[45] Hertwich EG, Hammitt JK (2001): Decision-analytic framework for impact assessment, Part 2: Midpoints, endpoints and criteria for method development. International Journal of Life Cycle Assessment 6, 265–272

[46] Bellman RE, Zadeh LA (1970): Decision-making in a fuzzy environment. Management Science 17 (4) B141–B164

[47] Weckenmann A, Schwan A (2001): Environmental life cycle assessment with support of fuzzy sets. International Journal of Life Cycle Assessment 6 (1) 13–18

[48] European Commission (1998): ExternE – Externalities of energy – Methodology Annexes. Common Annexes of the ExternE National Implementation Reports, Internet site <http://externe.jrc.es/append.pdf>. Luxembourg: European Commission, Directorate-General XII, Science, Research and Development, 1998

[49] Bare JC, Hofstetter P, Pennington DW, Udo de Haes HA (2000): Life cycle impact assessment workshop summary. Midpoints versus endpoints: the sacrifice and benefits. International Journal of Life Cycle Assessment 5 (6) 319–326

[50] Guinée JB, Gorree M, Heijungs R, Huppes G, Kleijn R, van Oers L, Wegener Sleeswijk A, Suh S, Udo de Haes HA, de Bruijn JA, van Duin R, Huijbregts MAJ (2001): Life cycle assessment: An operational guide to the ISO standards. Amsterdam, Netherlands, Kluwer Publishers

[51] Itsubo N, Inaba A (2003): A new LCIA method: LIME has been completed. International Journal of Life Cycle Assessment 8, 305

[52] Heijungs R, Goedkoop MJ, Struijs J, Effting S, Sevenster M, Huppes G (2003): Towards a life cycle impact assessment method which com-

prises category indicators at the midpoint and the endpoint level. Internet site <http://www.pre.nl/download/Recipe%20phase1%20final.pdf>. Amersfoort, Netherlands, PRé Consultants
[53] Hertwich EG, Hammitt JK (2001): Decision-analytic framework for impact assessment, Part 1: LCA and decision analysis. International Journal of Life Cycle Assessment 6 (1) 5–12
[54] Miettinen P, Hämäläinen RP (1997): How to benefit from decision analysis in environmental life cycle assessment (LCA). European Journal of Operational Research 102, 279–294
[55] Seppälä J, Basson L, Norris GA (2002): Decision analysis frameworks for life-cycle impact assessment. Journal of Industrial Ecology 5 (4) 45–68
[56] Noh J, Lee KM (2003): Application of multiattribute decision-making methods for the determination of relative significance factor of impact categories. Environmental Management 31 (4) 633–641
[57] Kühn I (1998): Non-environmental externalities. ExternE Newsletter <http:///externe.jrc.es/nletter6.html>, 6, 5–6
[58] Watson SR, Freeling ANS (1983): Comment on: Assessing attribute weights by ratios. Omega 11 (1) 13
[59] Dyer JS (1990): Remarks on the Analytic Hierarchy Process. Management Science 36 (3) 249–258
[60] Zimmermann HJ (1983): Using fuzzy sets in operational research. European Journal of Operational Research 13, 201–206
[61] Rahimi M, Weidner M (2004): Decision analysis utilizing data from multiple life-cycle impact assessment methods. Part II: Model development. Journal of Industrial Ecology 8 (1–2) 119–141
[62] Markandya A (1998): Accidents. ExternE Newsletter <http:///externe.jrc.es/nletter6.html>, 6, 5
[63] Krupnick AJ, Markandya A, Nickell E (1993): The external costs of nuclear power: ex ante damages and lay risks. American Journal of Agricultural Economics 75, 1273–1279
[64] Lenzen M, Munksgaard J (2001): Energy and CO_2 analyses of wind turbines – review and applications. Renewable Energy 26 (3) 339–362
[65] Intergovernmental Panel on Climate Change (2001): WGI third assessment report: summary for policymakers. Internet site <http://www.ipcc.ch/pub/spm22-01.pdf>. Geneva, Switzerland: Intergovernmental Panel on Climate Change
[66] Schoner B, Wedley WC (1989): Ambiguous criteria weights in AHP: consequences and solutions. Decision Sciences 20, 462–475
[67] Stewart TJ (1992): A critical survey on the status of multiple criteria decision making – theory and practice. OMEGA International Journal of Management Science 20 (5/6) 569–586
[68] Weber M (1997): Remarks on the paper 'On the measurement of preferences in the Analytic Hierarchy Process' by A. A. Salo and R. P. Hämäläinen. Journal of Multi-Criteria Decision Analysis 6, 320–321
[69] Fischer GW (1995): Range sensitivity of attribute weights in multiattribute value models. Organizational Behavior and Human Decision Processes 62 (3) 252–266
[70] Morgan MG, Morris S, Henrion M, Amaral DAL, Rish WR (1984): Technical uncertainty in quantitative policy analysis: a sulfur air pollution example. Risk Analysis 4, 201–216
[71] Rahimi M, Weidner M (2004): Decision analysis utilizing data from multiple life-cycle impact assessment methods. Part I: A theoretical basis. Journal of Industrial Ecology 8 (1–2) 93–118
[72] Keeney R, Raiffa H (1976): Decisions with multiple objectives. New York, USA, Cambridge University Press
[73] Udo de Haes HA (1999):. Weighting in life-cycle assessment. Is there a coherent perspective? Journal of Industrial Ecology 3 (4) 3–7
[74] Watson SR (1981): Decision analysis as a replacement for cost/benefit analysis. European Journal of Operational Research 7, 242–248
[75] Fischhoff B, Slovic P, Lichtenstein S, Read S, Combs B (1978): How safe is safe enough? A psychometric study of attitudes towards technological risks and benefits. Policy Sciences 9, 127–52
[76] Sagoff M (2000): Environmental Economics and the conflation of value and benefit. Environmental Science & Technology 34, 1426–1432
[77] Spash CL (2000): Multiple value expression in contingent valuation: economics and ethics. Environmental Science & Technology 34, 1433–1438
[78] Freeman A (1989): Ex ante and ex post values for changes in risk. Risk Analysis 9, 309–317
[79] Fischer GW, Damodaran N, Laskey KB, Lincoln D (1987): Preferences for proxy attributes. Management Science 33 (2) 198–214
[80] Hammitt JK (1999): Evaluation endpoints and climate policy: atmospheric stabilization, benefit-cost analysis, and near-term greenhouse-gas emissions. Climatic Change 41, 447–468
[81] Vargas LG (1994): Reply to Schenkerman's avoiding rank reversal in AHP decision support models. European Journal of Operational Research 74 (3) 420–425
[82] Schenkerman S (1994): Avoiding rank reversal in AHP decision support models. European Journal of Operational Research 74 (3) 407–419
[83] Eyre N (1997): External cost – what do they mean for energy policy? Energy Policy 25 (1) 85–95
[84] Slob W (1994): Uncertainty analysis in multiplicative models. Risk Analysis 14, 571–576
[85] Edwards W, Barron FH (1994): SMARTS and SMARTER: Improved simple methods for multiattribute utility measurement. Organizational Behavior and Human Decision Processes 60, 306–325
[86] Kirkwood CW, Sarin RK (1985): Ranking with partial information: a method and application. Operations Research 33 (1) 38–48
[87] Einhorn HJ, Hogarth RM (1975): Unit weighting schemes for decision making. Organizational Behavior and Human Performance 13, 171–192
[88] Stillwell WG, Seaver DA, Edwards W (1981): A comparison of weight approximation techniques in multiattribute decision making. Organizational Behavior and Human Performance 28, 62–77
[89] Barron FH, Barrett BE (1996): Decision quality using ranked attribute weights. Management Science 42 (11) 1515–1523
[90] Lundie S, Huppes G (1999): Environmental assessment of products - the ranges of social preferences method. International Journal of Life Cycle Assessment 4 (1) 7–15
[91] Saaty TL, Vargas LG (1987): Uncertainty and rank order in the analytic hierarchy process. European Journal of Operational Research 32 (1) 107–117
[92] Rosenbloom ES (1996): A probabilistic interpretation of the final rankings in AHP. European Journal of Operational Research 96, 371–378
[93] Limburg KE, O'Neill RV, Costanza R, Farber S (2002): Complex systems and valuation. Ecological Economics 41, 409–420
[94] Lenzen M, Dey CJ, Murray SA (2004): Historical accountability and cumulative impacts: the treatment of time in corporate sustainability reporting. Ecological Economics 51, 237–250
[95] Holling CS (1973): Resilience and stability of ecological systems. Annual Review of Ecology and Systematics 4, 1–23
[96] National Radiation Protection Board (1995): Risk of radiation-induced cancer at low doses and low dose rates for radiation protection purposes. Documents of the NRPB, Vol. 6, No. 1. Chilton, Didcot, Oxon, UK, NRPB
[97] Lenzen M, Wachsmann U (2004): Wind energy converters in Brazil and Germany: an example for geographical variability in LCA. Applied Energy 77, 119–130
[98] Curtiss PS, Rabl A (1996): Impacts of air pollution: general relationships and site dependence. Atmosphere and Environment 30, 3331–3347
[99] Lenzen M (2001): Errors in conventional and input-output-based life-cycle inventories. Journal of Industrial Ecology 4 (4) 127–148
[100] Suh S, Lenzen M, Treloar GJ, Hondo H, Horvath A, Huppes G, Jolliet O, Klann U, Krewitt W, Moriguchi Y, Munksgaard J, Norris G (2004): System boundary selection in Life-Cycle Inventories. Environmental Science & Technology 38 (3) 657–664
[101] Diamond PA, Hausman JA (1994): Contingent Valuation: is some number better than no number? Journal of Economic Perspectives 8 (4) 45–64
[102] Rosa LP, Schaeffer R (1995): Global warming potentials - the case of emissions from dams. Energy Policy 23 (2) 149–158
[103] Machina MJ (1987): Choice under uncertainty: problems solved and unsolved. Economic Perspectives (1) 121–154
[104] Tversky A, Kahneman D (1981): The framing of decisions and the psychology of choice. Science 211, 453–458
[105] Tversky A, Kahneman D (1986): Rational choice and the framing of decisions. Journal of Business 59 (4) S251–S278
[106] Tversky A, Simonson I (1993): Context-dependent preferences. Management Science 39 (10) 1179–1189
[107] Hershey JC, Kunreuther HC, Schoemaker PJH (1982): Sources of bias in assessment procedures for utility functions. Management Science 28 (8) 936–954
[108] Weber M, Camerer C (1987): Recent developments in modeling preferences under risk. OR Spektrum 9, 129–151
[109] Portney PR (1994): The Contingent Valuation debate: why economists should care. Journal of Economic Perspectives 8 (4) 3–17
[110] Carson RT (2000): Contingent Valuation: a user's guide. Environmental Science & Technology 34 (8) 1413–1418
[111] Haneman WM (1994): Valuing the environment through Contingent Valuation. Journal of Economic Perspectives 8 (4) 19–43
[112] Hammitt JK (2000): Valuing mortality risk: theory and practice. Environmental Science & Technology 34, 1396–1400
[113] Alberini A, Cropper M, Krupnick A, Simon NB (2004):. Does the value of s statistical life vary with age and health status? Evidence from the US and Canada. Journal of Environmental Economics and Management 48, 769–792

Recieved: December 21st, 2004
Accpeted: April 7th, 2005
OnlineFirst: April 8th, 2005

Appendix A: Uncertainty in the AHP

(Online edition only, see http://dx.doi.org/10.1065/lca2005.04.201)

Let the performance of alternative j in terms of indicator i expressed in its own physical units be denoted by P_{ij}. The AHP's first step is to make the decision problem independent of units by expressing the performance of alternatives as relative to each other, and normalise:

$$p_{ij} = \frac{P_{ij}^{\beta_i}}{\sum_k P_{ik}^{\beta_i}} \tag{1}$$

The exponent β_i indicates whether indicator i is desirable ($\beta_i = 1$) or undesirable ($\beta_i = -1$), so that a high p value indicates a good outcome. Second, the overall score s_j of alternative j is then the weighted sum over relative performances

$$s_j = \sum_i w_i p_{ij} \tag{2}$$

where the weights w_i are obtained in the conventional fashion through a pairwise comparison matrix, yielding an eigenvector $\boldsymbol{w}$ of weights that are normalised to satisfy $\Sigma_i\, w_i = 1$.

Assume that the indicators i may be located either at the interventions level, or at mid-, or endpoints. Rabl and Spadaro [41] have shown that for indicators resulting from multiplicative processes involving independent factors (such as in ExternE impact pathways), lognormally distributed observations around geometric means are most plausible (see also [84]). If the $P_{ij}^{\beta_i}$ in Eq. 1 are lognormally distributed, then the p_{ij} and s_j are also lognormally distributed. Their relative uncertainties can be calculated by first converting Eq. 1 to

$$\ln p_{ij} = \ln P_{ij}^{\beta_i} - \ln\left(\sum_k P_{ik}^{\beta_i}\right) \tag{3}$$

where the observations of the $\ln P_{ij}$ and $\ln p_{ij}$ are normally distributed so that

$$\Delta(\ln p_{ij}) = \sqrt{\sum_n \left(\frac{\partial(\ln p_{ij})}{\partial(\ln P_{in})}\Delta(\ln P_{in})\right)^2} \tag{4}$$

Inserting

$$\frac{\partial(\ln p_{ij})}{\partial(\ln P_{in})} = \delta_{jn}\beta_i - \frac{1}{\sum_k P_{ik}^{\beta_i}} \frac{\partial\left(\sum_k P_{ik}^{\beta_i}\right)}{\partial(\ln P_{in})}$$

$$= \delta_{jn}\beta_i - \frac{\frac{\partial\left(P_{in}^{\beta_i}\right)}{\partial(\ln P_{in})}}{\sum_k P_{ik}^{\beta_i}} = \delta_{jn}\beta_i - \frac{\beta_i\, P_{in}^{\beta_i}}{\sum_k P_{ik}^{\beta_i}} = \beta_i(\delta_{jn} - p_{in})$$

where δ_{jn} is the Kronecker symbol with $\delta_{jn} = 1$ if $j = n$ and $\delta_{jn} = 0$ otherwise, Eq. 4 becomes

$$\begin{aligned}\Delta(\ln p_{ij}) &= \sqrt{\sum_n \left(\frac{\partial(\ln p_{ij})}{\partial(\ln P_{in})}\Delta(\ln P_{in})\right)^2} \\ &= |\beta_i| \sqrt{\sum_n (\delta_{jn} - p_{in})^2\, \Delta(\ln P_{in})^2} \\ &= \sqrt{(1 - p_{ij})^2\, \Delta(\ln P_{ij})^2 + \sum_{n \neq j} p_{in}^2 \Delta(\ln P_{in})^2}\end{aligned} \tag{5}$$

The lognormal uncertainty of the scores s_j is then

$$\begin{aligned}\Delta(\ln s_j) &= \sqrt{\sum_n \left(\frac{\partial(\ln s_j)}{\partial(\ln p_{nj})}\Delta(\ln p_{nj})\right)^2} \\ &= \sqrt{\sum_n \left(\frac{w_n p_{nj}}{s_j}\Delta(\ln p_{nj})\right)^2}\end{aligned} \tag{6}$$

On the other hand, some indicator data (for example employment) or some dose-response functions ([41] p. 40) may derive from adding together survey or census samples that are normally distributed around an arithmetic mean. In this case, the relative uncertainty of the relative performances p_{ij} can be determined analytically through

$$\frac{\Delta p_{ij}}{p_{ij}} = \frac{\sqrt{\sum_n \left(\frac{\partial p_{ij}}{\partial P_{in}^{\beta_i}}\Delta P_{in}^{\beta_i}\right)^2}}{p_{ij}} \tag{7}$$

Inserting

$$\frac{\partial p_{ij}}{\partial P_{in}} = \frac{\delta_{jn}\beta_i P_{ij}^{\beta_i - 1}\sum_k P_{ik}^{\beta_i} - P_{ij}^{\beta_i}\,\beta_i P_{in}^{\beta_i - 1}}{\left(\sum_k P_{ik}^{\beta_i}\right)^2}$$

$$= \frac{\beta_i P_{ij}^{\beta_i}}{\sum_k P_{ik}^{\beta_i}} \frac{\delta_{jn} P_{ij}^{-1}\sum_k P_{ik}^{\beta_i} - P_{in}^{\beta_i - 1}}{\sum_k P_{ik}^{\beta_i}} = \beta_i p_{ij}\left(\frac{\delta_{jn}}{P_{ij}} - \frac{p_{in}}{P_{in}}\right)$$

Eq. 7 becomes

$$\frac{\Delta p_{ij}}{p_{ij}} = \left|\beta_i\right| \sqrt{\sum_n \left(\frac{\delta_{jn} \Delta P_{in}}{P_{ij}} - \frac{p_{in} \Delta P_{in}}{P_{in}} \right)^2}$$

$$= \sqrt{\left(1 - p_{ij}\right)^2 \left(\frac{\Delta P_{ij}}{P_{ij}} \right)^2 + \sum_{n \neq j} \left(p_{in} \frac{\Delta P_{in}}{P_{in}} \right)^2} \qquad (8)$$

The uncertainty of the scores s_j is then

$$\Delta s_j = \sqrt{\sum_i \left(w_i \Delta p_{ij} \right)^2} \qquad (9)$$

A complication arises when either within one impact pathway, or amongst indicators within a score, lognormal as well as normal distributions appear: Normal distributions allow (sometimes implausible) negative values, and mixed distributions can be of complex form, so that uncertainties can may not be evaluated analytically. In these cases, Rabl and Spadaro ([41] p. 40) suggest approximating a normal with a lognormal distribution so that their confidence intervals coincide.[27]

Finally, weights w_i may also be uncertain: Decision-makers may not be willing and/or able to provide specific enough or all of the required information,[28] or potential errors may occur when soliciting information from respondents, for example when respondents have not fully understood the definition or the significance of an indicator because of insufficient background information. A further variability may arise if the w_i represent societal values, with observations across respondents and over time distributed around a mean [90]. Incorporating parametrical uncertainty of the w_i into Eq. 9 is straightforward (see [91,92]), but it is not necessary to deal with this issue here because it does not add any new aspect to illustrating the midpoint/endpoint problem.

[27] If m is the mean of the normal distribution, and $d/2$ its 68%-confidence interval, the geometric standard deviation s_g of the lognormal distribution is then $\sigma_g^2 = (\mu + \delta/2)(\mu - \delta/2)^{-1}$.

[28] A class of multi-attribute decision methods therefore feature simplified procedures in which only a rank ordering is elicited from respondents (for example in SMART [85]; or lexicographic methods [86], and weights are inferred from ranks via unit weighting [87], rank sums [88] or rank-order centroids [89].